Retrieval and Verification of Deep Soil Moisture using Passive Microwave Data and a Temporal Variational Data Assimilation Method

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INTRODUCTION

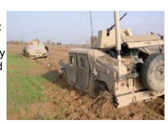
We have developed a four–dimensional coupled atmospheric/land data assimilation system using the Regional Atmospheric Mesoscale Data Assimilation System (RAMDAS) to retrieve deep soil moisture profiles. Passive microwave data from CORIOLIS WindSat is used as a surrogate for future microwave sensors.

Current efforts are focused on the use of the system for a case study occurring in September 2003. New adjoint sensitivity results using this system are presented, and implications for deep soil moisture retrievals using 4D variational (4DVAR) data assimilation systems are discussed. Using a variety of observational radiative transfer studies and spatial correlation analysis methods, we've also determined the statistical behaviors of the soil moisture field and microwave radiative transfer model performance that are necessary for performing the 4DVAR soil moisture data assimilation experiments. We conclude that additional radiative transfer model debiasing will be beneficial; however, polarization ratio results show a strong temporal soil moisture signal from the observational WindSat data sets that are able to be propagated by the adjoint sensitivities to soil depths greater than 1 m. Therefore deep soil moisture retrievals are shown to be feasible. We expect that advanced microwave emissivity analysis studies would provide more realistic constraints on behaviors of the surface microwave radiative transfer model parameters.

APPLICATIONS

This work contributes to several areas of interest:

1. More accurate probability estimates of mobility and trafficability
2. Improved hydrologic forecasting capabilities
3. Improved NWP land surface initialization
4. Better understanding of atmospheric/land interactions
5. More accurate agricultural assessments
6. Better in situ soil moisture quality control procedures



4DDA DEEP SOIL MOISTURE ESTIMATES

Direct remote sensing: Only Surface Soil Moisture
DA methods: Soil Moisture Profiles (up to 1m depths)

What makes this possible?

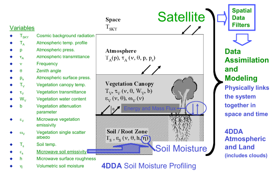
1. Diurnal soil moisture signal in land/atmos. physics
2. Use of temporal nature of the satellite data sets
3. Availability of good land surface models that can characterize the diurnal effects as a function of soil moisture

How long does it take to get results using the 4DDA method? Our results indicate that 7-14 days of integration time is necessary to reach 1 m soil depths, however shallower depths are reached in ~3 days of integration time or less. Some aspects of the 4DDA method is more immediate (for example, near the surface, new data impacts would be nearly immediate).

How is the WindSat data used? WindSat is sensitive to surface soil moisture variations. By matching those variations to the atmospheric/land surface model system, the soil moisture information in deeper levels can be inferred through its impact on the diurnal land/atmos. physics.

SOIL MOISTURE PHYSICS

Microwave Soil Moisture Physics



SOIL MOISTURE VERIFICATION

Our Oklahoma case study is selected for the month of September 2003. This month had good WindSat data coverage, availability of in situ soil moisture data sets, and wide-spread rain events which were easily observed by WindSat.

A geostatistical analysis was performed on the Oklahoma Mesonet in situ soil moisture station data and the Air Force Weather Agency's (AFWA) Agricultural Meteorology (AGRMET) soil moisture model output data. The spatial variability information is then used by a Kriging method to estimate soil moisture at unsampled locations. The spatial decorrelation length scale of soil moisture is critical for the initialization in multi-dimensional variational data assimilation research. The decorrelation length of soil moisture is seen to vary according to precipitation. Pre-precipitation regimes have a higher length than post-precipitation regimes indicating that precipitation storm-scales drive soil moisture spatial structures. In-situ measurement systems used in this study were found to be susceptible to quality control issues. Under such conditions, techniques such as the Kriging method described in this study can mitigate the quality control errors with appropriate geostatistical information. The effect of precipitation events on the spatial geostatistical structure (decorrelation length and sill) was also observed.

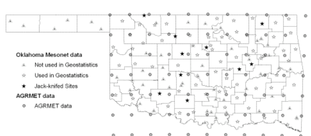


Figure 1: The distribution of AGRMET grid points and Oklahoma Mesonet sites used in the geostatistical analysis. The data is described in detail in Lakhankar et al. (2008).

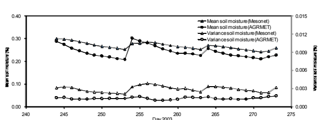


Figure 2: The mean and variance of soil moisture measured at Oklahoma Mesonet sites and AGRMET data for study area shows peaks after precipitation events on day 244, 254, 264.

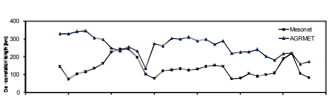
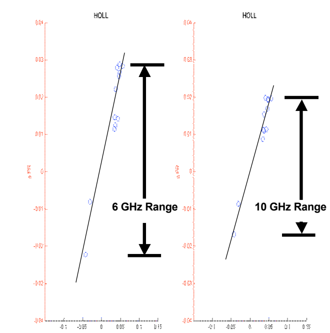


Figure 3: Spatial decorrelation lengths are higher for AGRMET model output compared to the Oklahoma Mesonet soil moisture data through the study period.

Table 1: This table shows the performance of Kriging in terms of volumetric soil moisture at each jack-knifed Mesonet site for September 2003. The jack knifing procedure is outlined in Lakhankar et al. (2008).

Site Name	Latitude	Longitude	Absolute Bias	RMSE	Correlation Coefficient
KETC	34.529	-97.765	0.059	0.060	0.81
KING	35.881	-97.911	0.027	0.030	0.97
LAHO	36.384	-98.111	0.006	0.008	0.94
MARE	36.064	-97.213	0.047	0.048	0.86
MAYR	36.987	-99.011	0.012	0.013	0.80
MEDI	34.729	-98.567	0.060	0.061	0.94
MINC	35.272	-97.956	0.023	0.026	0.86
NOWA	36.744	-95.608	0.027	0.032	0.46
OKEM	35.432	-96.263	0.025	0.026	0.86
OKMU	35.581	-95.915	0.011	0.013	0.91
All Sites	--	--	**0.030**	**0.032**	**0.84**

6 GHz vs. 10 GHz



Frequency Polarization Ratio Perturbations (ΔPR) vs. AGRMET Soil Moisture Perturbations (Δm_v): (left) 6 GHz, (right) 10 GHz.

WindSat observational results show that the 6 GHz channels are approximately 30% more sensitive to soil moisture than the 10 GHz channels.

This result was obtained by comparing temporal perturbations of the normalized polarization ratios (PR) to AGRMET model soil moisture values for the Hollis, OK (HOLL) site location (one of the RFI-free sites in OK). The AGRMET soil moisture temporal perturbation range for HOLL was ~10% in absolute SM units, or ~25% of the expected dynamic soil moisture range for the site. Larger rainfall events may have different frequency-dependent soil moisture responses due to soil saturation and surface flooding effects, etc.

WHAT ARE DEEP SOIL MOISTURE ADJOINT SENSITIVITIES?

Adjoints are used within variational data assimilation techniques to determine how to best adjust the model initial conditions to accommodate the observational sensor data information. Quantitatively a "cost function", *J*, is used to measure the distance that the model state is from the observational data. The adjoints are used to compute the gradients of the cost function. The gradient of the cost function is used to find the cost function minimum, so that the probability of the model state is maximized with respect to the observational data. Restated this is the most-likely model state given the data, and is our retrieval objective.

In time-dependent variational techniques such as 4DVAR, the cost function can be determined as a function of the temporally-integrated adjoint sensitivities. In our case, the control variables are the soil moisture at various soil depths. The adjoint sensitivities are computed with respect to these control variables. $\mathbf{L}(t_i, t_0)^T$, where **L** is the tangent linear operator of the forward model, **M** (see Eq. (3)). This information is combined with the model background and observational error covariance fields (**B** and **R**, respectively) and the observational operator, **H**, to determine the cost function gradient with respect to the model state initial conditions, **x** (t_0). The model background error covariance is estimated relative to "truth", as are the observational error covariance fields which are estimated instrument noise errors relative to "truth". The observational operator, **H**, transforms the model state information into the observational state (e.g., soil moisture and surface temperature model state information are transformed into passive microwave brightness temperatures).

The cost function gradient (Eq. 1) is the key factor which determines the new initial model state estimate. Thus, significant sensitivity within the adjoint integration demonstrates deep soil moisture retrieval feasibility given sufficient observational signal strength from the data (which WindSat already has already demonstrated for the surface soil moisture layers). For example, if the data indicate the model is off by amount "a" at time t_1, out of *N* data points, how much does the cost function (through its adjoint integration) indicate that the initial model conditions need to be adjusted to match this condition? It is interesting to note that the adjoints are integrated backwards in time. This is because we are interested in the propagation of data analysis increments, $[H(\boldsymbol{x}_i) - \boldsymbol{y}_i]$ back to the initial model time, t_0.

$$\frac{\partial J}{\partial \mathbf{x}(t_0)} = \mathbf{B}^{-1}\left[\mathbf{x}(t_0) - \mathbf{x}_b(t_0)\right] + \sum_{i=0}^{N} \mathbf{L}(t_i, t_0)^T \mathbf{H}_i^T \mathbf{R}_i^{-1} [H(\mathbf{x}_i) - \mathbf{y}_i] \quad (1)$$

$$\mathbf{H}_i = \frac{\partial H}{\partial \mathbf{x}_i} \quad (2)$$

$$\mathbf{L}_i = \frac{\partial M}{\partial \mathbf{x}_i} \quad (3)$$

$$\mathbf{x}(t_0) \quad (4)$$

ADJOINT SENSITIVITY RESULTS

The single-observation adjoint sensitivities, $\mathbf{L}^T$, are shown in Fig. 4. For this 21-day experiment, 13 additional WindSat data observations were available for multi-temporal analysis. Thus, the single-observation results are conservative indicators of the ability of WindSat to detect deep soil moisture, as the additional data points would increase the deep soil moisture signal strength through repeated views of the scene. We show the single observation adjoint results as they are simpler to interpret. The adjoints are integrated backwards in time from day 21 to the initial condition time, $t = 0$. The results are normalized adjoint sensitivities, determined by dividing the temporal adjoint sensitivity result by the largest soil layer sensitivity. This means that at any one time, one soil layer will have 100% relative adjoint sensitivity strength relative to the other soil layers. What is most important is the relative sensitivity of each layer. As we follow the backwards integration, the leadership of the sensitivity strength changes from the top soil layer to the deepest soil layer (1.2 m – 0.6 m) (see Fig. 4). This transition occurs within a period of 7-14 days. By the initial conditions, the bottom three layers at 1.2 m, 0.6 m, and 0.3 m, contribute 100%, 65%, and 35% of the signal strength respectively. The surface layers all contribute less than 20% at the model initial time. This means that surface information from earlier time periods are much more important to the determination of the deep soil moisture values, as expected.

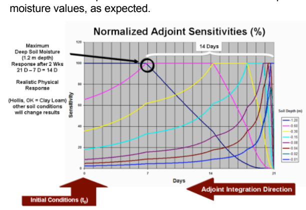


Figure 4: Normalized adjoint sensitivity results for Hollis, OK for the Sep. 2003 case study. Deep soil moisture at a depth of approximately 1 m has the largest sensitivity in the integration time period of 0-7 days. This indicates the strong deep soil moisture sensitivity as a function of soil depth with time.

CONCLUSIONS

Our conclusions are:

1) **Deep soil moisture retrievals using temporal variational techniques are feasible.**
   a) 21-day integration experiments demonstrated very strong adjoint sensitivities.
   b) The adjoint soil moisture sensitivity to the initial soil moisture conditions show a variety of time scales according to soil depth and as a function of soil type.
2) **WindSat and future NPOESS surface soil moisture retrievals can be extended to lower depths using this technique.**
   a) The RAMDAS 4DVAR data assimilation results were successful at creating the components necessary for full 4DVAR WindSat data assimilation capabilities for deep soil moisture retrievals.
   b) A full 21-day adjoint integration study was successfully performed for a single point observation to determine depth profile feasibility issues.
3) **Future Work**
   a) We recommend that future work focus on 14-21 day experiments. For operational use, 2DVAR methods would be more computationally efficient and flexible for use in decentralized computational environments.
   b) Observational radiative transfer model (RTM) parameter sensitivity studies and radiometric bias estimation using WindSat indicate that the RTM bias is 5-8 K, which is higher than the instrument noise. Thus microwave RTM improvements and bias corrections are needed. This should be done by observationally retrieving microwave surface emissivities to improve the RTM parameterizations and related physics.

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